Precision dairy technologies for organic and low-input dairy production systems

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ABSTRACT

The use of precision dairy technologies for the management of confinement dairy cattle has been well documented. Less work has been conducted on evaluating precision dairy technologies within pasture-based dairy herds in the United States. The potential of precision dairy technologies to be utilized in pasture-based dairy herds was evaluated at the West Central Outreach and Research Center in Morris, MN, organic grazing and low-input conventional dairy herds. An ear-attached accelerometer was validated for accuracy of recording rumination, eating and activity behaviors in pasture-based dairy crossbred cows. Activity and rumination were recorded by an activity and rumination collar system from January 2014 to December 2017, and purebred Holsteins were compared with crossbreds. Because activity and rumination monitoring collars have improved estrus detection in confinement dairy herds, the estrus detection performance of a collar system was evaluated in an organic grazing dairy herd and a low-input conventional herd by breeding season.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LITERATURE REVIEW

Introduction

Pasture-based dairy herds continue to grow in the Unites States as the demand for grass-fed and sustainable farming practices increases. Sustainability may be achieved in confinement dairy herds; however, the increased expense of dairy farming has triggered producers to adapt different management styles within their herds. Welfare and cow comfort must be a priority within pasture-based dairy herds; however unlike in confinement barns, cattle are not always within eye sight of employees. Precision dairy technologies (PDT) allow for cattle to be monitored all the time without the constant presence of a person. Monitoring daily behaviors such as feeding, ruminating, resting or lying, and active time can aid in understanding animal health and productivity. Producers that want to increase overall production efficiency, should consider implementing PDT, as decision making may improve and labor costs tend to decrease (Bikker et al., 2014).

Pasture-based dairy herd management

According to the USDA-NASS 2016 organic certified survey, in the United States, there are over 260,000 certified organic milking cattle of which 42,000 cattle are in the Upper Midwest (USDA-NASS, 2017). The organic dairy industry has grown over the past 10 years and with the increased demand of organic dairy products, interest from the consumers concerning animal welfare and herd management of organic dairy farms compared to conventional dairy farms is anticipated (Stiglbauer et al., 2013). The National Organic Program (NOP), requires organic dairy producers **(ORG)** to manage their cattle differently than conventional dairy producers **(CONV)**. Most CONV dairy herds in the United States tend to have cattle housed in barns throughout the entire year.

In ORG herds, for 120 d of the year all cattle including young stock, 6 mos of age and greater, must consume 30% or more of their daily dry matter intake from pasture and have access to the outdoors throughout the entire year (USDA-NOP, 2017). In the Upper Midwest, weather constraints force cattle to graze from May to November, and for the rest of the year cattle are typically housed in a barn or outdoor lot where they are fed a total mixed ration.

A research study in Minnesota, surveyed ORG and CONV herds and compared management characteristics of each. ORG herds tended to use a breeding bull, whereas CONV herds did not, and age at first calving was lower in CONV herds compared to ORG. Most of the CONV herds evaluated, provided heat abatement such as misters or sprinklers to their cattle compared to ORG herds. Kelp was an ingredient that ORG herds used to feed their cattle that CONV herds did not (Sorge et al., 2016). ORG, CONV non-grazing and CONV grazing herds across various regions of the United States were surveyed from 2009 to 2011. Major differences reported by the survey included higher grain intake and milk production in the CONV herds compared with the ORG herds. Treatment records were better maintained, there was less use of veterinarians, lower DHIA participation and less interaction with nutritionists in the ORG herds (Stiglbauer et al., 2013). Interaction with nutritionists may be lower in ORG herds because pasture is the main feed source during the grazing months. Pasture-based producers must know how to maintain high quality pastures as grazing activity has been reported to cost in general 10 to 25% of animal maintenance energy (Gregorini et al., 2008). Pasture-based dairy cattle need energy to be able to walk from the pasture to the milking parlor and graze daily for 8 to 10 hrs. Grazing is usually performed in bouts of 1.5 to 2 hrs, and repeated 4 to 5 times throughout the day (Ungerfeld et al., 2014).

Environmental effects such as heat stress and fly pressure during the summer months are some of the challenges pasture-based dairy cattle have to adapt to, compared to confinement dairy cattle. During the summer in the Upper Midwest, the temperature humidity index (THI) rises above 72, defined as the start of mild heat stress in Holstein dairy cattle, and often times can rise to a THI of 78, considered as extreme heat stress in dairy cattle (Soriani et al., 2013; Palacio et al., 2015). Fly management in pasture-based dairy farms, but more specifically in organic dairy farms, is challenging because the use of synthetic pesticides is prohibited. The horn fly, typically found on the back along the spine of cattle, and stable fly, found on the lower leg of cattle are harmful biting flies that tend to appear in large quantities during the summer (Sjostrom et al., 2016). Even when shade is provided, fly intensity does not tend to change because odor released by cows is what attracts flies (Palacio et al., 2015).

Heat stress and fly pressure may decrease daily dry matter intake which decreases rumination time (Soriani et al., 2013), and increases daily activity (Sjostrom et al., 2016). Holstein cattle in an Italian confinement research herd were utilized to evaluate changes in rumination time during heat stress. The authors reported that for every unit of THI above a threshold of 76 THI, rumination decreased 2.2 min/d (Soriani et al., 2013). In Minnesota, a study was conducted with an organic dairy research herd, and during the summer, activity was greater in July (1258 activity units), and rumination was lower in July (361 min/d; $P < 0.05$) compared to June, August and September. During September, daily activity decreased and daily rumination increased with a slight decrease in temperature (Sjostrom et al., 2016). Unless cattle are brought into a barn or provided shade on pasture, heat stress may affect pasture-based cattle by increasing daily activity and decreasing dry matter intake, eventually decreasing rumination time. Drastic changes within activity and rumination time in confinement cattle during heat stress may occur less, as most confinement barns tend to have heat abatement or cooling mechanisms (Soriani et al., 2013; Sorge et al., 2016).

Changes in temperature throughout the day can also affect when cattle choose to graze. Digestibility and palatability of certain forages may be affected by the loss of moisture, therefore pasture-based dairy cattle tend to consume the majority of their meals near sunrise and sunset (Gregorini et al., 2006). When cows are allocated to a new pasture or return from milking, they graze for the first few hours and then ruminate (Gregorini et al., 2009). The social behavior of Holstein dairy cows was explored from 2010 to 2011 in Uruguay. The pasture-based study, reviewed that less dominant grazed away from areas in which more dominant cattle grazed. Dominant cattle had a larger bite rate and would feed faster, and began ruminating while less dominant cattle continued to graze (Ungerfeld et al., 2014).

Breeds for pasture-based dairy production

Pasture-based diets tend to be lower in energy, and in New Zealand where grazing is a popular method, Jersey cattle tend to be favored for their small body size, fat and protein yield and fertility. An increase in grazing time has been reported, as Jerseys tend to present an “aggressive grazing aptitude” (Prendiville et al., 2010). Because of the greater production yield, Holsteins tend to graze for longer periods of time to compensate for energy needs or often need to be supplemented with concentrates (Hessle et al., 2014). Many studies in New Zealand have reported that crossbreeding Jerseys with Holsteins increases profitability, as crossbreds tend to be more efficient grazers than purebred Holstein cattle (Buckley et al., 2014).

Pasture-based dairy producers prefer crossbred cows to Holsteins (Sato et al., 2005). This is supported by Sorge et al. (2016), who reported ORG herds in Minnesota are comprised of 60% crossbreds and 37% Holsteins. Although Holsteins are the most popular dairy breed in the United Sates because of higher milk yields (Paz et al., 2016), pasture-based dairy cattle naturally tend to have lower production (Sorge et al., 2016). Higher milk yields have negatively affected fertility of the Holstein breed, and higher pregnancy rates are especially important to seasonal pasture-based dairy producers (Walsh et al., 2008). Therefore, fewer days open and fewer number of services might be of greater interest to grazing producers, which is something that crossbreds may provide (Hazel et al., 2017). Breeds from Scandinavian countries such as Denmark and Sweden have always incorporated fertility in genetic programs (Walsh et al., 2008). Normande × Holstein, Montbéliarde × Holstein, and Scandinavian Red × Holstein crossbreds were evaluated in California on commercial dairy herds for survival and profitability. The crossbreds survived longer than the Holsteins and provided greater projected lifetime profit. However, Normande × Holstein crossbreds had lower projected lifetime profit compared to Holsteins, which may suggest that these crossbreds could be better utilized in grazing herds (Heins et al., 2012). The use of Normande cattle has been explored in grazing herds. Compared to Holstein cattle, Normande cows had a shorter calving interval and higher conception rate. In seasonal grazing systems, cows have a shorter window period to get bred, and the Normande breed could be beneficial (Cutullic et al., 2009).

Alternative breeds such as the Viking Red, Normande and Montbéliarde, have gained popularity and are being used for crossbreeding in dairy herds across the United States in both grazing and confinement herds. In Ireland where seasonal grass-based production is common, the Montbéliarde and Normande breeds have provided economic efficiency through increased solid production and improved beef quality (Buckley et al., 2014). Swedish Mountain cows were compared to Holsteins in Sweden within an intensive grazing system, and Holsteins had higher energy requirements for maintenance. In addition, GPS data were recorded and Holstein cattle tended to travel less while grazing, while Swedish Mountain cows walked farther and for longer when grazing (Hessle et al., 2014).

Potential of precision dairy technologies for pasture-based dairy herds

Precision dairy farming is an area that has focused on improving dairy farm performance (Borchers and Bewley, 2015). Automated milking systems continue to be the most popular, however precision dairy technologies that can record behaviors of individual cattle have grown in popularity (Rutten et al., 2013). Different behaviors such as feeding or grazing, rumination, temperature and activity status of individual animals can be recorded, however, technologies that help detect mastitis and estrus, in addition to monitoring milk yield are the most valuable to producers. To invest in technologies, producers value the profitability, investment cost and how easy they will be to use (Borchers and Bewley, 2015). This is not surprising because technologies that provide estrus alerts, monitor milk yield or mastitis tend to be straightforward; the farmer must either breed or not breed the cow, check the cow for any abnormal signs that may cause fluctuations in milk yield or check for mastitis. Technologies that might require interpretation of results to make a decision might be less popular (Rutten et al., 2013).

Many PDT attach to the cow and may be reused. Cow behavior data may be continuously collected by the PDT, and depending on the technology, raw data is processed inside the specific technology through an algorithm or transferred to a computer for processing. Raw data may be transferred from PDT to computers by infrared or radio frequency. These routers can be connected to electricity or use solar power, which is often beneficial in pasture-based herds. Once raw data are processed through algorithms or calculations it can be categorized into specific behaviors or health and estrus alerts. The data can then be viewed on a computer system, on a website and some companies have applications for mobile devices (Rutten et al., 2013; Pereira et al., 2018).

Organic dairy producers in the United States cannot use hormones to synchronize their cattle for estrus behavior, and no antibiotics may be used. Treatment with antibiotics can be performed in emergencies (USDA-NOP, 2017); however, the animal cannot return to the herd. Because animal welfare is still a concern in ORG dairy herds, PDT could provide measures to associate welfare and comfort in ORG herds (Rutten et al., 2013). Lying time has been explored to determine cow comfort when shade was provided during the summer in pasture-based dairy cattle. When THI was above 72, the onset of heat stress, an increase in lying time and grazing time was observed in cows that had access to shade compared to cows that had no shade access (Palacio et al., 2015). Reproductive management may facilitate, as PDT have detected the start of estrus through monitoring the increase of physical activity (Løvendahl and Chagunda, 2010). Reproductive management may also decrease in cost as the use of hormones for estrus synchronization could be reduced by investing in PDT (Michaelis et al., 2013).

Producers that are considering investing in a PDT find that the performance of the PDT when supported by research that is independent of the parent company is just as important as ease of use and total investment cost (Borchers and Bewley, 2015). Because there are so many PDT available, experimental studies across different dairy systems may indicate advantages or disadvantages of certain PDT which could be valuable to dairy producers. Validation studies are commonly used to determine how PDT record certain behaviors (Borchers et al., 2016). Behaviors recorded by the PDT are compared to behaviors recorded by an individual or cameras. A correlation can be calculated between visually recorded behaviors and behaviors recorded by the PDT. A strong correlation indicates that a certain behavior was accurately recorded by the PDT when compared to for example, visual observation. Hinkle et al. (2003), defined correlations as such, negligible: 0.00 to 0.30; slight: 0.31 to 0.50; minor: 0.51 to 0.70; moderate: 0.71 to 0.90; and strong: 0.91 to 1.00.

The HR-LD Tag (SCR Engineers Ltd., Netanya, Israel), which is worn around the neck of cattle includes a microphone which records regurgitation and chewing activity in minutes per day and an accelerometer that determines the daily activity of individual animals. A strong correlation (0.93) between rumination time recorded by the HR-LD Tag and visual observation was achieved in an University research confinement herd comprised of Holsteins (Schirmann et al., 2009). Elischer et al. (2013) validated the same PDT with Holstein cows in a pasture-based robotic herd. A moderate correlation (0.61) was reported between activity recorded by the tag and visual observations, and a correlation of 0.65 between rumination time recorded by the tag in comparison to visual observation. Another study found that in outdoor conditions, microphone recording of jaw movements and sounds may be disturbed by the environment (Andriamasinoro et al., 2016). Grazing can be a complicated behavior to define because cattle can be moving slowly or stay still while picking through or consuming pasture (Ungerfeld et al., 2014).

The CowManager sensor (Agis Automatisering BV, Harmelen, the Netherlands), is an ear-tag which includes an accelerometer that records ear and head movements and classifies them into ruminating, eating, resting and active behaviors. The sensor has been previously validated, accurately detecting ear and head movements compared to visual observation in a confinement herd in the Netherlands (Bikker et al., 2014). The author previously mentioned, reported correlations between the sensor in comparison to visual observations of 0.93 for rumination, 0.88 for eating, 0.98 for resting, and 0.73 for active. In the study, the correlation for active behavior was lower than the other behaviors, as ear movements associated with active behavior may be more complex to classify unlike rumination a fairly repetitive ear movement (Bikker et al., 2014). More recently, the same sensor was validated in a confinement research dairy herd in the Unites States with 46 lactating cattle. A correlation of 0.88 for rumination and 0.69 for feeding time were achieved between the sensor and visual observation (Borchers et al., 2016). The sensor was validated on beef steers in an outdoor feedlot, and rumination time was recorded as feeding time by the sensor, particularly when head movements for fly avoidance were displayed (Wolfger et al., 2015).

Estrus detection and predicting estrus events from precision dairy technologies

Visual signs of estrus behavior include standing to be mounted, mounting behavior, chin resting and sniffing of the vulva (Reith and Hoy, 2017). These behaviors tend to be performed by multiple cattle, including cattle that are not experiencing estrus (Palmer et al., 2010). Decreased duration of estrus behavior within the Holstein breed has been documented (Cutullic et al., 2009; Valenza et al., 2012; Fricke et al., 2014), and visual observation of estrus detection is on average around 50% in most dairy herds. In herds that have a lower estrus detection rate, PDT have proven to provide a higher rate than visual observation at detecting estrus (Valenza et al., 2012; Fricke et al., 2014).

Activity monitoring systems can measure daily activity of dairy cows and may detect 70-80% of cows in estrus (Fricke et al., 2014; Leroy et al., 2018). The PDT may provide a specific breeding window for optimal time to artificial insemination (AI), and recent studies have indicated that cows that are inseminated 16 h after an activity monitoring system generates an estrus alert, have a greater probability of becoming pregnant (Leroy et al., 2018). Seasonally calving herds have a short breeding period, and cows that calve later in the season might only have 1 or 2 estrus events that may be visually observed (Cutullic et al., 2009). Therefore, reproductive efficiency of dairy cows is important within seasonally calving systems (Walsh et al., 2008). When several cows are in heat, which is typically experienced in seasonal calving herds, estrus is better expressed making visual detection of estrus usually easier for producers (Chanvallon et al., 2014). Visual observation of estrus detection may be time consuming, labor intensive and not as accurate, while using PDT may increase efficiency. Larger dairy herds that tend to breed cows once a day versus twice a day may benefit from PDT to provide correct breeding windows. A recent review by Roelofs and van Erp-van der Kooij (2015), reported that AI should be performed 5 to 17 h from the time an estrus alert is provided by activity monitoring systems. Once a day versus twice a day AI may still lead to pregnancies per AI for most cows, but as examined in Leroy et al. (2018), to maximize probability of pregnancy in first lactation cows, insemination should occur very shortly after an estrus alert is generated by the activity monitoring system.

As reported by Steeneveld and Hogeveen (2015), the use of PDT for estrus detection is very popular for producers in the Netherlands. In Germany, producers acknowledged that estrus detection rate has increased since the installation of their PDT (Michaelis et al., 2013). Common PDT that can detect estrus in dairy cattle include accelerometers and pedometers. Pedometers are worn on the feet of cattle, recording the number of steps (Reith and Hoy, 2017). Accelerometers are typically found inside ear-tags measuring accelerations of ear and head movements (Bikker et al., 2014), or neck collars measuring accelerations of neck and head movements (Elischer et al., 2013). Some precision dairy technologies may record more than one behavior, and in fact when two or more behaviors are recorded, estrus detection tends to be more accurate than with activity alone (Kamphuis et al., 2012; Reith and Hoy, 2017). A study in Germany, described that 94% of the estrus events analyzed had a decline in rumination time during estrus behavior, with the average decrease of 74 min/d per cow (Reith and Hoy, 2012).

Research studies have evaluated the performance of many PDT for estrus detection by comparing the estrus alerts generated by PDT to a gold standard. Gold standards vary by research study, but many tend to use visual observation often times with the help of Estrotect™ heat patches (Rockway Inc., Spring Valley, WI) or tail paint

(Kamphuis et al., 2012; Roelofs and van Erp-van der Kooij, 2015). Friction from mounting behavior rubs-off the patch or tail paint and cattle may be evaluated for AI based on how much has rubbed off, which is described in Palmer et al. (2010). Progesterone levels in blood or milk during estrus are considered the gold standard when evaluating performance of activity monitoring systems. Although progesterone measurements are accurate and very valuable in research studies, progesterone analysis is expensive and not as practical for producers (Rutten et al., 2013). Producer considerations are extremely important as they will be investing in the PDT. Conducting research studies on producer farms may not always be a choice, so research studies that mimic the use of a PDT on farm could be beneficial. A field study with pedometers and neck collars in producer confinement herds evaluated pedometers and neck collars. The study reported that some producers choose to ignore a certain percentage of estrus alerts by the activity monitoring system based on absent signs of estrus and because irregular activity was indicated (i.e. moving cows to a new pen or hoof trimming). However, the low progesterone in the blood samples demonstrated that those cows could have been bred resulting in pregnancies (Leroy et al., 2018).

When evaluating a PDT, a high number of necessary and low number of unnecessary estrus alerts should be generated by the PDT. A true positive (TP) is when an estrus alert corresponds with a true estrus event. If there was no estrus alert and there was a true estrus event, this was considered a false negative (FN). A false positive (FP) is when a true estrus event does not occur, but an estrus alert did. Less non-estrus alerts are optimal so the farmer isn’t having to check cows that are not actually in estrus or having extra insemination costs. When no estrus alerts are generated by the technology or true estrus events are recorded, those are considered as true negatives (TN) (Roelofs et al., 2017). The sensitivity (SN), specificity (SP) and positive predictive value (PPV) can indicate the level of performance certain technologies obtain. Greater SN indicates the technology is detecting almost all of the true estrus events designated by the gold standard The SP should be close to 100 as true estrus events should not missed. When the PPV is greater, less non-estrus alerts (false estrus events) are being declared by the technology The performance of PDT for estrus detection varies based on the defined gold standard (Roelofs and van Erp-van der Kooij, 2015) and may depend on the environment and herd management (Saint-Dizier and Chastant-Maillard, 2012). An acceptable SN would be greater than 80%, an SP closer to 100% and a PPV closer to 80% if not greater than the SN. In confinement dairy systems, PDT have achieved higher SN (94%) for estrus detection, however, in pasture-based systems SN seems to be lower (Roelofs and van Erp-van der Kooij, 2015).

The increase of physical activity leading up to ovulation has been thoroughly described with the use of activity monitoring systems (Valenza et al., 2012; Fricke et al., 2014). Because estrus detection through the use of PDT can be subjective to management and environment, a prediction model could be valuable. Estrus prediction (Martiskainen et al., 2009; Dolecheck et al., 2015) and calving prediction models (Borchers et al., 2017) have been explored in confinement herds through machine and algorithm learning.

Models that are to be implemented in a commercial setting need to exceed in performance evaluated through values SN and SP, generate an ideal response time, i.e. hours from when an alert was generated to when a cow should be inseminated and the models should consider practicality, for producers will need to implement these on a daily basis (Hogeveen, et al., 2010). A model commonly utilized for estrus detection is the Support Vector Machine (SVM). The SVM is a statistical method that can use collected data and through pattern recognition, trains an algorithm to classify data (Martiskainen et al., 2009) into different levels of activity which can be utilized to predict estrus (Yin et al., 2013). To train the predictor model typically 80% of already collected data are used for training the algorithm and 20% for testing the performance of the activity monitoring system.

Precision dairy technologies and genetics

Grazing behavior may be affected by body size, breed, environment, stocking density and even social hierarchy. Smaller cattle tend to have a smaller grazing bite, spending more time grazing compared to other breeds (Vance et al., 2012). Different breeds of cattle such as the Jersey and Holstein-Friesian may be pastured together without disturbing grazing behavior within the breeds (Prendiville et al., 2010).

Although rumination time may be different for different breeds, most cattle tend to ruminate on average anywhere from 400 to 600 min/d (Bae and Welch, 1983; Prendiville et al., 2010; Braun et al., 2015; Stone et al., 2017). Pasture-based dairy cattle in New Zealand were evaluated, and Holstein-Friesians ruminated for a longer period of time (426 min/d) compared to Jerseys (371 min/d). This was explained by the smaller bolus size made by the Jersey (Prendiville et al., 2010). Because Jersey cows are able to ruminate for a shorter amount of time, rumination time may not be as compromised during heat stress compared to other breeds (Stone et al., 2017). Dairy cattle housed in tie-stall barns (n=300) were all fed the same hay, corn silage/haylage and concentrate diet and Brown Swiss cows ruminated for 405 min/d, Holstein Friesians for 458 min/d and

Swiss Fleckvieh for 460 min/d (Braun et al., 2015). In a recent study, Holstein and Jersey lactating cattle displayed dissimilar rumen bacterial communities, suggesting that different dairy breeds may not process feed particles alike (Paz et al., 2016).

The use of activity monitoring systems has been used to record duration and strength as well as frequency of estrus events. In Denmark cattle were equipped with activity neck tags, and Holstein and Red Dane cattle displayed stronger and longer estrus events compared to Jerseys. As recorded by the activity tag, Red Dane cattle displayed an estrus event much earlier than the other two breeds (Løvendahl and Chagunda, 2010). Daily activity unlike rumination time has been less evaluated across breeds and research studies, as many studies use activity to study the behavior around estrus (Dolecheck et al., 2015). Recently, a study conducted from 2011 to 2013 in Kentucky, evaluated daily activity of primiparous and multiparous Holstein, Jersey and crossbred cattle in a confinement research herd. Primiparous cattle tended to display greater activity, explained by displacement in the feed bunk. However within the multiparous group, crossbreds had significantly greater daily activity (341 activity units) than Jerseys (307 activity units) and Holsteins (263 activity units) (Stone et al., 2017).

Conclusions

Precision dairy technologies have provided novel information about activity, rumination and grazing behavior of various breeds, however references of intervals for activity and rumination of crossbreds should be explored. Precision dairy technologies have the potential to maximize profit for dairy producers as significant improvement has been made so they can be implemented in various dairy systems. However, improvement of precision dairy technologies for pasture-based dairy herds needs to continue as the number of herds continue to grow. Grazing is a behavior that should continue to be explored with precision dairy technologies. Estrus detection with the utilization of activity monitoring systems in organic dairy herds is not as precise, and activity monitoring systems should be utilized as a supplementary aid. Estrus prediction models can be helpful as behavioral differences may alter how technologies perform and adapt, varying by environment and management.

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MANUSCRIPT 1

Technical note: Validation of an ear-tag, accelerometer sensor to determine rumination, eating and activity behaviors of grazing dairy cattle.

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INTERPRETIVE SUMMARY

Technical note: Validation of an ear-tag, accelerometer sensor to determine rumination, eating and activity behaviors of grazing dairy cattle. Pereira et al., (2017). The objective of this study was to validate an ear-attached accelerometer (individual cow sensor) to monitor rumination, eating and activity behaviors in pasture-based cows. This technology effectively measured rumination and eating time, but was less effective in measuring activity behaviors in pasture-based systems.

SUMMARY

The objective of this study was to validate an ear-tag, accelerometer sensor (CowManager SensOor, Agis Automatisering BV, Harmelen, the Netherlands) using direct visual observations in a grazing dairy herd. Lactating crossbred cows (n = 24) were used for this experiment at the University of Minnesota West Central Research and Outreach Center grazing dairy in Morris, Minnesota during the summer of 2016. A single trained observer recorded behavior every min for 6 h for each cow (24 cows x 6 h = 144 total h of observation). Direct visual observation was compared to sensor data during August and September 2016. The sensor detected and identified ear and head movements, and through algorithms, the sensor classified each minute as one of the following behaviors: rumination, eating, not active, active and high active. A 2-sided t-test was conducted with PROC TTEST of SAS to compare the percentage of time each cows' behavior was recorded by direct visual observation and sensor data. For total recorded time, the percentage of time of direct visual observation compared to sensor data were 17.9% and 19.1% for rumination, 52.8% and 51.9% for eating, 17.4% and 11.9% for not active and 7.9% and 21.1% for active. Pearson correlations (PROC CORR of SAS) were used to evaluate associations between direct visual observations and sensor data. Furthermore, concordance correlation coefficient (CCC), bias correction factors (Cb), location shift (V) and scale shift (μ) (epiR package of R software) were calculated to provide a measure of accuracy and precision. Correlations between visual observations for all 4 behaviors were highly to weakly correlated (r = 0.72, CCC = 0.71 for rumination; r = 0.88, CCC = 0.88 for eating; r = 0.65, CCC = 0.52 for not active; and r = 0.20, CCC = 0.19 for active) compared to sensor data. The results suggest that the sensor

accurately monitors rumination and eating behavior of grazing dairy cattle. However, active behaviors may be more difficult for the sensor to record than others.

Key words: precision technology, pasture, behavior monitoring, rumination

TECHNICAL NOTE

Individual cow technologies may be used to measure rumination and feeding time, health status of cows (Bikker et al., 2014), as well as activity for estrus detection of dairy cattle. Pasture-based systems are becoming more common in the US dairy industry (USDA, 2016), and grazing dairy producers may benefit from utilizing precision dairy technologies. However, the majority of work conducted with precision technologies has been in confinement systems. In this regard, environmental and management conditions such as walking activity and fly pressure may affect how accurately these technologies work in grazing systems (Elischer et al., 2013; Ambriz-Vilchis et al., 2015; Sjostrom et al., 2016).

The objective of this study was to validate the CowManager ear-tag sensor (CowManager SensOor, Agis Automatisering BV, Harmelen, the Netherlands) in a grazing dairy herd by comparing direct visual observations and sensor data for rumination, eating, not active and active cow behaviors. The hypothesis of this study was that ruminating behavior would have greater correlation between direct visual observations and sensor data than eating, not active, or active behaviors.

During the summer of 2016 (August to September), 24 crossbred cows (4 Holstein-sired, 4 Jersey-sired, 3 Montbéliarde-sired, 5 Normande-sired and 8 Viking Red-sired crossbred cows) at the University of Minnesota West Central Research and Outreach Center, Morris, Minnesota dairy herd were utilized for the study. The total number of cows needed for the experiment was determined using power analyses with a power of 0.80 and 95% confidence level (Friedman, 1982). The current study evaluated more cows than the original CowManager validation study conducted by Bikker et al. (2014), and had more cows than recent validations of precision dairy technologies for pasture-based systems (Elischer et al., 2013; Ambriz-Vilchis et al., 2015).

Cows were offered pasture for 22 h each day. Cows were milked twice per day at 0600 and 1700 h in a swing-9 parabone-milking parlor. The pastures were comprised of diverse grasses and legumes that included smooth bromegrass, orchardgrass, meadow fescue, alfalfa, red clover and kura clover. Cows were stocked at a rate of 3 cows/ha, with 4,019 kg DM/ha available at the initiation of grazing and were rotated to new paddocks every 2 d based on forage availability. Grazing was initiated at 20-30 cm ± 2-3 cm (mean ± SD) and leaving 7-9 cm ± 2-3 cm refusals. In addition to pasture, each cow was daily supplemented with 2.72 kg of organic corn and had free-choice access to minerals from a feeder placed at ground level in each paddock. Cows had ad libitum access to water from a water trough also placed at ground level in each paddock.

All cows were equipped with the CowManager ear-tag sensor for 6 mo to 1 yr before the study began. The sensor was mounted into a blank Radio Frequency Identification tag (eliminating any interference with the system) first, and then placed on the right ear of each cow. Data from the sensor were sent wirelessly through a plug and play router or solar router to a coordinator in the milking parlor and made available through a web-based application (Bikker et al., 2014). Agis Automatisering BV (Harmelen, the Netherlands) provided raw hourly data for the ruminating, eating, not active and active behaviors for all cows. The sensor detected and identified ear and head

movements and through algorithms classified data as ruminating, eating, not active, active and high active behaviors. We did not include high active behavior because it may be associated with estrus behavior which we did not record in the current study.
All direct visual observations were recorded by a single trained observer throughout the study. Prior to the initiation of the study, behavior definitions were agreed upon on site by 4 observers – an experienced ethologist, 2 trained observers, and the observer that was conducting the visual observations for the study. These definitions were based on previous research studies and the ethologist's training.

Rumination was defined when a cow was either lying, standing or walking, and the cow regurgitated a bolus and chewed the cud while moving her head and jaw in a circular motion and then swallowing the masticated cud. If the cow was observed not regurgitating or chewing for more than 10 sec, this behavior was considered finished (Elischer et al., 2013). Eating was when a cow had eating jaw movements and the muzzle was in close contact with the ground (Nielsen, 2013), and the cow may have been walking at the same time. Eating mineral, corn and drinking water was considered eating behavior. Not active was when a cow was standing or lying on the ground and did not consume feed, ruminate, or perform any activity (Elischer et al., 2013; Bikker et al., 2014). Active was when a cow stood on all 4 legs and the cow walked or moved her body (Mullens et al., 2006; Bikker et al., 2014). During the observation period, each minute was considered to be only 1 of 4 behaviors (ruminating, eating, not active or active). Behaviors were mutually exclusive and if a cow was eating and walking, she was only considered as eating. If the cow performed two behaviors during the minute of observation, the behavior she performed the longest during that minute was the predominant behavior (Rutten et al., 2017). Only if the cow performed 2 behaviors for exactly 30s each during the minute of observation, those minutes would be identified as transitional and would not have been included in the analysis.

All 24 cows were observed for a total of 6 h/cow (24 cows x 6 h = 144 total h of observation). The observer had a 1 h break between observation times to control for fatigue. Each cows' predominant behavior during every minute was recorded by the observer on a Microsoft Excel 2016 (Microsoft Corp., Redmond, WA) spreadsheet. Time was recorded on observation sheets and a digital watch (Timex, Timex Group USA, Inc., Middlebury, CT) was used to track time. The average temperature, humidity and dew point during the study were 21.4°C, 76.8% and 16.5 °C, respectively.

The UNIVARIATE procedure (SAS, 2014) was used to establish normality. A 2-sided t-test (PROC TTEST) was conducted to compare the percentage of time each cows' behavior was recorded by direct visual observation and sensor data. Pearson correlations between direct visual observations and sensor data were analyzed with the CORR procedure of SAS. The concordance correlation coefficient (CCC; Lin, 1989), bias correction factors (Cb), location shift (V) and scale shift (μ) were calculated with the epiR package of R software (R version 3.3.1, R Foundation for Statistical Computing, Vienna, Austria). The CCC was calculated to determine the accuracy of correlations between direct visual observations and sensor data. Over prediction of the location shift results in negative values and an under prediction of location shift may be expected with a positive value (Bikker et al., 2014). Pearson correlations and CCC were considered negligible (0.00 to 0.30); slight (0.31 to 0.50), minor (0.51 to 0.70); moderate (0.71 to 0.90); and strong (0.91 to 1.00), as described by Bikker et al. (2014).

The percentage of total time for direct visual observation and sensor derived behaviors, along with the median and 95% confidence intervals are presented in Table 1. The time a cow was ruminating ($P = 0.57$) and eating ($P = 0.77$) was similar for direct visual observation compared to the sensor. The percentage of time a cow was not active was greater (17.4% versus 7.9%; $P = 0.04$) for direct visual observation compared to the sensor. Active behavior tended to be lower (11.9% versus 21.1%; $P = 0.10$) for direct visual observation compared to the sensor, respectively. Median values are closely aligned with the percentage of time for behaviors. Range in confidence intervals was similar between visual observations and the sensor.

Table 2 has correlations, bias correction factor, CCC, location shift and scale shift of direct visual observations compared to sensor data. The correlation of rumination between direct visual observation and sensor was 0.72 ($P < 0.01$; CCC = 0.71). Borchers et al. (2016) reported a correlation and CCC of 0.69 and 0.59, respectively, and Bikker et al. (2014) reported a correlation and CCC of 0.93, and both studies were conducted in a free-stall barn. Although the correlation of rumination in the current study is similar to Borchers et al. (2016), they reported that rumination was the most difficult behavior to evaluate across the various observers. This may explain the lower correlation (0.69) observed by Borchers et al. (2016). However, in the current study ($r = 0.72$) there was only 1 observer compared to the previously reported studies. A lower correlation for rumination behavior observed in the current study may be due to the observer not accurately observing and recording rumination behavior. Elischer et al. (2013) reported that in a grazing system it might be difficult to accurately record rumination behavior because a cow’s head may not always be within view of the observer. The high correlation for rumination in this study indicates that the sensor records rumination time accurately.

Eating behavior of direct visual observations and sensor data were highly correlated ($r = 0.88$, $P < 0.01$; CCC = 0.88). Bikker et al. (2014) ($r = 0.88$, CCC = 0.75) and Borchers et al. (2016) ($r = 0.88$, CCC = 0.82) found similar results to the current study for eating behavior. The differences in CCC may be due to the difference in the number of observers utilized in each individual study. Eating time may be properly identified by the sensor in a pasture-based system.

An association was found between not active behavior of direct visual observation and sensor data ($r = 0.65$, $P < 0.01$; CCC = 0.52). Active behavior had the lowest correlation of direct visual observations and sensor data ($r = 0.20$, $P < 0.01$; CCC = 0.19). The lower correlation observed for active behavior may have been because of hot and humid weather. Because the sensor records ear movement patterns via an accelerometer, not active and active behaviors may be more difficult to record than other behaviors. Grazing may be considered both an active and eating behavior because cows may graze while standing or while walking (Nielsen, 2013). Precision dairy technologies are more capable of recording precise and accurate behaviors than a human observer, which may also explain the weaker correlations between direct visual observation and the sensor for active behaviors (Rutter et al., 1997).

To our knowledge, this is the first validation study evaluating direct visual observation compared to CowManager sensor data for a grazing dairy herd. Results of the current study indicate that grazing dairy producers may use the sensor to monitor cows' rumination and eating time. We suggest that precision technology companies continue to work on improving behavior detection along with updating software algorithms to provide producers with reliable and accurate information at all times. Furthermore, more research needs to be conducted to determine how individual cow technologies define grazing behavior.

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Table 1. Total recorded time (± SD) as a percentage of time for behaviors from direct visual observations[1] compared to CowManager sensor[2] data of cows on pasture

	Visual			Sensor			*P*-value
Item	Total time ± SD	Median	95% CI	Total time ± SD	Median	95% CI	
Rumination	17.9 ± 8.2	16.8	14.4 to 21.3	19.1 ± 7.3	18.81	16.0 to 22.1	0.57
Eating	52.8 ± 14.5	52.36	46.7 to 59.0	51.9 ± 13.6	55.53	46.2 to 59.0	0.77
Not Active	17.4 ± 11.8	13.74	12.5 to 22.4	7.9 ± 7.6	5.26	4.7 to 11.1	0.04
Active	11.9 ± 5.5	11.25	9.6 to 14.2	21.1 ± 7.8	18.81	17.8 to 24.4	0.10

[1]Visual observations and CowManager were compared on an hourly basis.
[2]CowManager SensOor ear tag (Agis Automatisering BV, Harmelen, the Netherlands).
Results were conducted with a 2-sided paired t-test.

Table 2. Results of a validation study with Pearson correlation coefficient (r), bias correction factor (C_b), concordance correlation coefficient (CCC), location shift (V) and scale shift (μ) of direct visual observations[1] compared to CowManager sensor[2] data of 24 crossbred dairy cattle[3]

Item	Correlation	P-value	Correction bias (C_b)	CCC	Location shift (V)	Scale shift (μ)
Rumination	0.72	<0.001	0.99	0.71	-0.06	1.13
Eating	0.88	<0.001	0.99	0.88	0.02	1.11
Not Active	0.65	<0.001	0.81	0.52	0.61	1.38
Active	0.20	<0.05	0.96	0.19	-0.19	0.80

[1]Visual observations and CowManager were compared on an hourly basis.
Direct visual observations were recorded every minute for a cow (data were recorded for a total of 6 h/cow).
[2]CowManager SensOor ear tag (Agis Automatisering BV, Harmelen, the Netherlands).
[3]Cows were 4 Holstein-sired, 4 Jersey-sired, 3 Montbéliarde-sired, 5 Normande-sired and 8 Viking Red-sired crossbreds.

MANUSCRIPT 2

Estrus detection with an activity and rumination monitoring system in an organic grazing and low-input conventional dairy herd.

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INTERPRETIVE SUMMARY

Estrus detection with an activity and rumination monitoring system in an organic grazing and low-input conventional dairy herd. Pereira et al. (2018). This study evaluated estrus detection of an activity and rumination monitoring system in an organic pasture-based dairy herd and a low-input conventional herd. Estrus detection by the activity and rumination monitoring system was more accurate during the winter months than during the summer months for the organic herd, while it was equally accurate among the winter and summer months for the low-input conventional herd.

SUMMARY

The objective of the study was to evaluate estrus detection from an activity and rumination system (ARS) in a seasonal calving organic grazing (ORG) and low-input conventional (CONV) dairy herd. Additionally, data provided by the ARS was used with machine learning techniques to create an estrus prediction model. The study period spanned from June 2014 to August 2017 at the University of Minnesota West Central Research and Outreach Center, Morris, MN. Because cows calve seasonally in the experimental herd, cows were also bred seasonally. Cows that calve during the spring are bred during the summer and cows that calve during autumn are bred during the winter. The study had 4 summer breeding seasons (June to August) and 3 winter breeding seasons (December to February). During each breeding season, activity and rumination (daily and 2-h blocks of time) were monitored electronically using HR-LD tags (SCR Engineers Ltd., Netanya, Israel). Activity (neck and head movement) was reported in activity units, and rumination was reported in minutes per 2-h block and minutes per d from SCR DataFlow II software. All cows were fitted with an HR-LD tag at calving and the tag remained on the cow until dry off. Estrus alerts of individual cows provided by the SCR DataFlow II software were used to determine if the alert agreed with the breeding date of a cow. The gold standard for this study were breeding dates of cows that were determined by breeder evaluation of an Estrotect™ patch placed on the rump of a cow. The study included 1,463 breeding dates across the 4 yrs. The ARS had a sensitivity of 56.7%, a specificity of 99.3% and a positive predictive value of 59.8% for the ORG herd, and a sensitivity of 70.1%, a specificity of 99.2% and a positive predictive value of 66.3% for the CONV herd across breeding seasons. The custom models illustrated the

potential range of sensitivity and specificity that can be achieved with these data. Adjusting the threshold of estrus detection may provide the producer more control of generated estrus alerts depending on the breeding season. The ARS evaluated in this study showed potential for estrus detection within grazing and low input dairy herds.

Keywords: automated estrus detection, grazing, low-input dairy

INTRODUCTION

Reproductive efficiency of dairy cattle is of high importance to maintain a profitable dairy herd, especially for grazing production systems. A short breeding season puts enormous pressure on a farmer to achieve a high level of estrus detection in seasonally calving grazing systems. Recently, detection of estrus through visual observation has become challenging, especially with a shorter duration of estrus behavior in high producing dairy cows (Talukder et al., 2015). Although the most common sign of estrus behavior is standing to be mounted, some cows do not experience standing heats (Roelofs et al., 2010), making visual observation, patches and tail paint use challenging if a breeding program is not well managed.

Precision dairy technologies such as activity monitoring systems have the ability to measure daily activity of cattle, and these systems have been largely successful for estrus detection (Madureira et al., 2015; Talukder et al., 2015; Reith and Hoy, 2017). Most precision technology manufacturers develop proprietary algorithms to create alerts when cows are in estrus. Activity and rumination systems **(ARS)** tend to provide more accurate results than activity monitoring systems alone for estrus detection (Kamphuis et al., 2012; Reith and Hoy, 2017), because rumination time tends to decrease on the day of estrus (Reith and Hoy, 2012).

Previous studies have explored the use of machine learning for estrus detection (Martiskainen et al., 2009; Dolecheck et al., 2015) and calving prediction (Borchers et al., 2017) as a way to replace or supplement proprietary algorithms. Custom prediction models may be particularly useful if proprietary algorithms struggle to accommodate specific circumstances of management or climatic conditions of the dairy herd. Given that manufacturer's provision of information for the farmers under unconventional circumstances generallly lags behind, it is important to investigate to what extent and how those farmers may effectively utilize the technology.

Activity monitoring systems have shown to be practical for dairy farm use; however, enormous variation exists between sensitivity for estrus detection performance, especially within pasture-based dairy herds by (Roelofs and van Erp-van der Kooij 2015). Previous research studies have evaluated estrus detection with activity monitoring systems and custom prediction models, however these were done during a short period of time or with small cows numbers (Kamphuis et al., 2012; Dolecheck et al., 2015; Roelofs et al., 2017). Recent studies have evaluated ARS in pasture-based dairy herds, but there is a lack of studies that have evaluated ARS in organic dairy herds. Although estrus detection performance of an ARS has been compared in a pasture versus indoor period in the Netherlands (Roelofs et al., 2017), there is a lack of information on how ARS function in the Upper Midwest during the hot summer grazing period and cold winters.

Therefore, the objectives of the study were to 1) evaluate the estrus detection potential of an ARS in a seasonal calving organic grazing and low-input conventional experimental dairy herd, and 2) utilize data provided by the ARS to compare the performance of custom models by logistic regression and Support Vector Machine to the performance of a proprietary ARS algorithm.

MATERIALS AND METHODS

The study was conducted at the University of Minnesota West Central Research and Outreach Center, Morris, MN and animal care and management were approved by the University of Minnesota Institutional Animal Care and Use Committee (#1508-32966A). Data spanned 4 summer breeding seasons, (June 2014 to August 2014, June 2015 to August 2015, June 2016 to August 2016, June 2017 to August 2017), and 3 winter breeding seasons, (December 2014 to February 2015, December 2015 to February 2016 and December 2016 to February 2017). The 300-cow research dairy herd is divided into an organic grazing **(ORG)** and low-input conventional **(CONV)** herd. The herd is comprised of purebred Holsteins, 1964 genetic control purebred Holsteins and crossbreds of Holstein, Montbéliarde and Viking Red, and crossbreds of Jersey, Normande and Viking Red. Cows were milked twice per day in a swing-9 parabone-milking parlor. The ORG herd was milked at 0600 h in the morning, followed by the CONV herd at 0800 h and the ORG herd was milked at 1700 h in the evening followed by the CONV herd at 1900 h.

During the grazing season (May to October), the ORG herd was offered pasture for 22 h a day according to the National Organic Program pasture rule (USDA-NOP, 2017), which requires ORG dairy cattle to graze for at least 120 d and for cows to receive at least 30% of DMI from pasture. The pastures were a mixture of diverse grasses and legumes that included smooth bromegrass, orchardgrass, meadow fescue, alfalfa, red clover, white clover, and kura clover. Cows were stocked at a rate of 3 cows/ha, and cows were rotated to new paddocks every 2 d based on forage availability. Grazing was initiated at 20-30 cm and grass was grazed to 7-9 cm. In addition to pasture, each cow was supplemented with 2.72 kg of organic corn daily and had free-choice access to minerals from a feeder placed at ground level in each paddock. Cows had ad libitum access to water from a water trough also placed at ground level in each paddock. During the winter months (November to April), ORG cattle were moved to an outwintering lot (Heins et al., 2018) and fed a TMR consisting of organically-raised corn silage, alfalfa haylage, corn, soybean meal, and minerals in feed bunks within the outwintering lot. For the CONV herd, cattle were fed a TMR consisting of conventional corn silage, alfalfa haylage, corn, soybean meal, and minerals in an outdoor confinement dry-lot during the summer and a compost-bedded pack barn during the winter (Heins et al., 2018).

Herd management

The ORG and CONV herds calved seasonally and were bred to maintain a seasonal production system. Calving seasons were spring (March to May) or autumn (September to November) and breeding seasons were summer (June to August) or winter (December to February). The start and end dates of these seasons were consistent throughout the study. Estrotect™ heat patches (Rockway Inc., Spring Valley, WI) and the ARS were utilized to monitor estrus behavior. Certified organic dairy farms cannot use synchronization hormones (USDA-NOP, 2017); therefore, no hormones were used to induce estrus for the ORG cattle. Cattle in the CONV herd that were anestrus were enrolled in a CIDR-Sync program (CIDR; InterAg, Hamilton, New Zealand); however, 90% of CONV cows were bred as a result of natural heat.

Estrotect™ patches were placed on all cows in the ORG and CONV herd once their DIM were greater than the voluntary waiting period of 55 DIM. The ARS were assigned to a cow at the time of calving. Cows were not allowed to be bred until the first day of the breeding season even if the ARS detected an estrus event before the start date of the breeding season because of the seasonal calving system of the 2 herds. Visual evaluation of Estrotect™ patches was done during milking, when cattle were near the holding area of the milking parlor. All farm staff were trained to report and record cows that were being mounted and in standing heat. Cows were only bred during the morning after cows exited the milking parlor. Nebel et al. (1994) reported that once a day breeding provides similar non-return rates to traditional twice a day breeding. If a cow was observed mounting during any other time, on pasture, in the compost barn, dry lot or during the afternoon milking, cow identification and estrus observation was recorded and the cow was evaluated the following morning based on her Estrotect™ patch. Every day of the breeding season, trained farm staff first reviewed cows eligible for breeding according to the ARS and then according to the Estrotect™ patch. Specifically, cows that were deemed eligible for breeding by the ARS were evaluated for their Estrotect™ patch by methods described in Palmer et al. (2010). If a cow was determined to be eligible for breeding by the ARS but not by Estrotect™ patch, the cow's cervix was evaluated for tone and a breeding decision was made by the farm staff. Pregnancy diagnoses were conducted biweekly during the breeding season by a veterinarian using ultrasonography and began 28 d after the first breeding date of the season.

Editing and collection of data

At calving, all cows were equipped with an HR-LD tag activity and rumination collar (SCR Engineers, Netanya, Israel). Activity (reported in “activity units” by daily and bihourly periods) and rumination (reported in min/d and min/2 h period), were monitored by a tri-axial accelerometer, microphone and microprocessor contained within the collar tag. The HR-LD tag transferred data to a long distance antenna placed atop the milking parlor. The antenna had a range of several hundred meters, depending on the weather and other environmental factors. Each time the cattle returned to the milking center, and if they were in paddocks near the milking center, the antenna would download data as often as every 20 min. The data were sent to the computer in the farm office and processed through the SCR DataFlow II software (Data Flow Software, SCR Engineers, Netanya, Israel). Data from the computer was downloaded weekly into a Microsoft Excel worksheet. The HR-LD tag has been previously validated for rumination in a confined herd recording rumination accurately (Schirmann et al., 2009), and in a grazing robot herd (Elischer et al., 2013) the tag recorded activity and rumination, but not as accurately as previous validations.

Cow data (herd, breed group, lactation number, calving dates, breeding dates, and pregnancy check dates) were retrieved from PCDart software (Dairy Records Management Systems, Raleigh, NC). Cows with lactations greater than 5 were excluded from the analysis. Only cows that were eligible to be bred during a given breeding season were included in the analysis. A total of 531 cows were included in the analysis, and 499 of the 531 cows were bred at least once during the study, and 32 of the 531 cows were not bred during the study (Table 1). Some cows had multiple lactations within the 4 yr span of the study period, and cows in the current study had 953 lactations (374 primiparous lactations and 579 multiparous lactations) (Table 1). The final dataset had a total of 1,463 breeding dates. The ARS provided estrus alerts on 64.5% (n = 944) of the breeding dates, and 33.5% (n = 519) of the breeding dates did not have alerts provided by the ARS. About half of the herd was eligible to be bred in a given breeding season, and the other half was pregnant throughout the season. Because we did not have confirmation from progesterone concentration in milk or blood that a cow was in estrus or anovular as other studies have utilized (Valenza et al., 2012), cows that were not bred were included in the analysis. Anovular cows have been used previously for prediction of ovulation with an ARS in a pasture-dairy herd (Talukder et al., 2015), and therefore, it is important to include anovular cows in the analysis. A benefit of investing in an ARS, is that the system may provide estrus alerts for cows that may have irregular cycles that cannot be visually observed.

In seasonal calving herds, there is a short period of time for farmers to get cows pregnant. A seasonal breeding herd in New Zealand reported 71% of their herd pregnant after 42 d of breeding using tail paint and heat patches (Kamphuis et al., 2012). A study in Switzerland compared reproduction efficiency of Holstein-Friesian, Fleckvieh, Brown Swiss and New Zealand Holstein-Friesian cows in a pasture-based system. The authors reported 90% pregnancy rates at the end of the 12 wk mating season and the first-service conception rate was 60% (Piccand et al., 2013). In the current study, 73% of cows in the ORG herd and 74% of the cows in the CONV herd were pregnant after the breeding season. Perhaps, the ORG herd experienced heat stress while on pasture during the hot summer months and environmental affects reduced fertility. Reith and Hoy (2017) reviewed multiple studies which reported that cattle were less likely to become pregnant during long and short-term heat stress periods. However, because most of the ORG and CONV herds are comprised of crossbreds, greater pregnancy rates may have been achieved than most herds with this type of housing and management system. Walsh et al. (2008) found crossbreds in a pasture system had greater pregnancy rates at the end of the breeding season compared with Holstein-Friesians.

Statistical analysis

Sensitivity **(SN)**, specificity **(SP)** and positive predictive value **(PPV)** were calculated with PROC SQL of SAS (SAS Institute, 2014) to determine the ARS estrus detection performance. Visual estrus detection from Estrotect™ patches was the gold standard. Rump-mounted friction patches have proven to perform similarly to activity monitors for estrus detection (Valenza et al., 2012; Sauls et al., 2017). Visual observation with the aid from tail paint was used as a method to detect estrus in previous studies comparing estrus detection characteristics in pasture versus confinement Holstein-Friesian cows in an Irish research herd. A similar number of estrus events were recorded by visual observation and the pressure mounted device on pasture (Palmer et al., 2010).

The performance of the ARS was assessed based on whether it provided an appropriate estrus alert within a time window of 48 h, including on the day of estrus (d 0) or the day before estrus (d -1). All dates, either breeding or non-breeding, were examined for whether an appropriate estrus alert was provided by the ARS. The four possible outcomes were a true positive (**TP**, a breeding date with an alert), a false negative (**FN**, a breeding date with no alert), a false positive (**FP**, a non-breeding date with an alert), and true negative (**TN**, a non-breeding date with no alert). During a breeding season there were days when no cows were bred and no ARS estrus alerts were generated. Those days were considered TN and were used in calculations to determine the ARS performance (Roelofs et al., 2017). Calculations of ARS performance were; sensitivity = TP/(TP+FN) x100; specificity = TN/(TN+FP) x100; and positive predictive value = TP/(TP + FP) x100. The PROC FREQ function in SAS was used to calculate the 95% confidence intervals for SN, SP and PPV.

Prediction Models

Custom estrus prediction models (logistic regression and support vector machine **(SVM)** models) were developed by combining ARS data and cow data, including herd (ORG or CONV), breed group, lactation number, breeding season (summer or winter), and breeding and pregnancy records, where the dependent variable was estrus status supplied by the breeding date. The logistic regression is highly scalable with the data and is suitable for deriving various tradeoff relationships between SN and SP in the predicted outcome. The SVM has a clear mathematical formulation and is known to perform reliably across diverse types of data and dataset sizes in the machine-learning literature (Cortes and Vapnik, 1995; Steinwart and Chirstmann, 2008).

The bihourly observations of the ARS data were converted into daily observations of the 24 h sums, 4 h window sums, and the daily maximums of 4 h window sums of activity and rumination. The interaction variables were defined on the standardized activity and rumination variation at each combination of herd type, season, and hour to account for simultaneous changes in activity and rumination with estrus. All data were analyzed for the 24 h cycle of estrus detection, starting at 0800 h. Data were processed further to enhance prediction performance, and additional variables were constructed. This process involved removing noise to isolate signals in the raw ARS data (i.e., differences from the daily herd average), creating variables that represent deviations from normal (i.e., 1, 3, 5, and 7 d moving-averages and 7, 14, and 21 d window standard deviations), and specifying varying coefficients across herd, breed group, and breeding season.

Variable selection was assessed in comparison to alternative specifications that included a set of more rigorously processed versions of the data. Specifically, the mixed models for rumination and activity were estimated with fixed effects of interactions of breeding season and herd, breeding season and breed group, and breeding season and lactation number and cow was nested within herd and parity as a random effect. The implied repeatability by cow random effects accounted for 40% of the rumination and 77% of the activity random deviation from the daily herd averages. Of these variables made available to the extended models, the least absolute shrinkage and selection operator (**LASSO**) was used to select a relevant set of variables. The LASSO is a common and effective technique to assess the impact of dropping individual variables and simplify the model specification in machine learning (Tibshirani, 1996). Significant differences between the base and the extended models would indicate the need for additional control variables in the base model.

All models were estimated on a training subset of the data or a random sample of the data comprising 80% of the observations, and all results were assessed on a testing subset of the data, or the remaining 20%. Logistic regression was called by glm and SVM functions of the e1071 package, and LASSO from the glmnet package of R software. All analyses of prediction models were conducted with R statistical software version 3.3.1 (R Foundation for Statistical Computing, Vienna, Austria).

RESULTS AND DISCUSSION

The estrus detection performance results from the ARS (SN, SP and PPV) for the ORG and CONV herds are in Table 2. Additionally, 95% confidence intervals are reported for SN, SP, and PPV. For the ORG herd results, including the summer and winter breeding seasons, were 56.7% for SN, 99.3% for SP and 59.8% for PPV (Table 2). The results were similar to those reported by Kamphuis et al. (2012), who reported a SN of 67.4%, a SP of 99.0%, and a PPV of 72.0% with the same neck collar ARS in a pasture-based dairy herd in New Zealand. One possibility for relatively lower SN and PPV in the current study compared to those obtained in previous studies may be due to the differences in the method of establishing gold standard estrus detection. While it is common for researchers to use progesterone as an indicator of estrus, such measurements are rarely available to farmers or they are not economically feasible for most dairy producers. The gold standard for estrus detection used in the current study closely mimicked a typical breeding practice on dairy farms, and hence the results had direct relevance to dairy farmers.

For the ORG herd, the ARS had lower performance during the summer breeding season (33.8% for SN, 99.3% for SN and 47.9% for PPV) compared to the winter breeding season (79.2% for SN, 99.3% for SP and 66.8% for PPV). The current ARS performance was highly comparable to a typically reported SN of 80% in most dairy herds (Michaelis et al., 2014). The increased variability of walking distances by cows depends on grazing rotations, and this change in activity may have contributed to decreased accuracy by the ARS for estrus detection during the summer breeding season (Verkerk et al., 2001; Saint-Dizier and Chastant-Maillard, 2012). In particular, FP alerts by the ARS tend to increase at the beginning of a grazing season due to the change of housing conditions (Roelofs et al., 2017).

For the CONV herd, the overall SN was 70.1%, the SP was 99.2% and the PPV was 66.3% across summer and winter breeding seasons. The performance during the summer breeding season (69.3% for SN, 99.2% for SP and 66.8% for PPV) was similar to the winter breeding season (71.3% for SN, 99.3% for SP and 67.3% for PPV). This was expected because the cows in the CONV herd walked the same route between the milking parlor and the confined outdoor areas during the summer and winter.

The results of the current study for SN and PPV are comparable to other studies that have evaluated SN (72% to 90%) and PPV (67% to 78%) for dairy cattle on pasture (Roelofs and van Erp-van der Kooij, 2015). Conversely, a study conducted during 2014 and 2015 in the Netherlands evaluated a ARS system in a pasture and confinement system. The authors reported no difference in SN and PPV between the pasture and confinement period, and the ARS had a SN of 78% for the confinement period which was similar to the current study for the CONV herd (Roelofs et al., 2017). During the winter breeding season for the CONV herd, the SN and PPV was slightly lower than the ORG herd. The ORG herd was housed closer to the milking parlor during the winter breeding season and had to walk a short distance to the milking parlor. Therefore, activity levels were not as high for the ORG herd compared with the CONV herd during the winter.

The current study did not observe a higher SN in the ORG and CONV herd with the 48 h time period allowed for estrus alerts compared to previous studies. Perhaps, the time window provided for estrus alerts generated by the ARS could have been increased, because Kamphuis et al. (2012) reported increased performance of the ARS with a greater time frame around a true estrus event. Cows in both the ORG and CONV herd may have experienced heat stress and fly pressure during the summer (Sjostrom et al., 2016), which may have affected some of the variation in the SN and PPV of our study compared to other studies. Furthermore, the current study reported a greater number of FP than other studies which may be due to the constant activity change or because some cows that are not in estrus exhibit mounting behaviors on cows that are in estrus (Palmer et al., 2010).

Prediction models

The results of four predictive models, including two logistic regression models and two SVM models, were similar for SN and SP, and no single model had dominant performance over others in all cases (Table 3). For the logistic regression models, binary prediction results were obtained at a threshold of 65% predicted probability of estrus, at which the results between the logistic and SVM models were highly comparable. Additional variables used in the extended models did not seem to provide much additional predictive power. No improvement by SVM over logistic regression and by the introduction of additional variables in the extended models, appeared to indicate successful model specification for the base models.

Across herds and breeding seasons, the model performances were similar among the ORG winter breeding season (90.4% for SN and 97.4% for SP under logistic regression), the CONV summer breeding season (81.4% for SN, 95.1% for SP) and the CONV winter breeding season (83.9% for SN, 97.0% for SP), all of which were superior to the ARS performance for the ORG summer breeding season (60.0% for SN, 91.1% for SP). Receiver operating characteristic curve under the base model logistic regression showed that these relationships also held for a wide range of the SN and SP (Figure 1). For each curve, selected tradeoffs are marked at the thresholds of 60%, 65%, and 70% predicted probability of estrus. The higher the threshold, the lower the SN and the higher the SP. The effect of the threshold on the SN-SP tradeoff is large for the ORG summer breeding season, moderate for CONV summer breeding season, and low for CONV and ORG winter breeding seasons. The SN and SP for ORG summer breeding season is 67.1% for SN and 83.9% for SP at the 50% threshold, 61.4% for SN and 89.0 for SP at the 60% threshold, 51.4% for SN and 93.5% for SP at the 70% threshold.

It is important to compare the performance between the proprietary alert system and the custom model predictions. The custom models have a tendency greater SN and lower SP compared to the proprietary alert, albeit the performance of the two systems can be similar to each other at a fixed SN or SP. For producers who wish to choose an alternative tradeoff between SN and SP, a commercial system typically allows for adjustments in threshold parameter.

Key factors affecting the optimal SN and SP tradeoff include visual inspection time on FP alerts, decision rules for replacing cows due to the failure to conceive, and current estrus detection SN (Rutten et al., 2014). Under ORG dairy production, challenges with estrus detection during the grazing season appear to imply that it is economically optimal to target a higher SN and lower SP combinations than the implicit target by the default-setting proprietary alert system. That is, when those factors vary over seasons, the producer may want to adjust alert thresholds with seasons. In the current study, the optimal threshold was lower in summer (40 to 45% of the probabilities of estrus predicted by logistic regression) than in winter (60 to 65%). Also, it may make economic sense for some producers to develop a supplemental alert system by combining ARS data and a custom algorithm. Custom prediction models may be developed with daily breeding records that are reliable enough to serve as a gold standard measure of estrus.

CONCLUSION

The accuracy of estrus detection by an ARS system was high in a low-input CONV dairy herd, but the results were mixed and depended on breeding seasons in an ORG grazing herd. In the ORG herd, the ARS was able to detect estrus accurately in the winter breeding season but not in the summer breeding season. The custom estrus prediction models evaluated were comparable to the proprietary alert system. Because the environment and management of a dairy farm may alter the performance of estrus detection by activity monitors, independent research that closely mimics producer experiences should continue to be conducted.

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Table 1. Number of cows and lactation observations[1] by specific breed groups for the organic and low-input conventional dairy herds at the University of Minnesota West Central Research and Outreach Center, Morris, MN

	Total number of cows	Primiparous lactations			Multiparous lactations		
		Organic	Conventional	Total	Organic	Conventional	Total
Breed							
Holstein	96	17	41	58	10	102	112
1964 Holstein	71	30	20	50	46	32	78
Holstein-sired crossbred	77	20	25	45	26	86	112
Jersey-sired crossbred	50	24	6	30	56	6	62
Montbéliarde-sired crossbred	73	28	39	67	15	41	56
Normande-sired crossbred	32	20	7	27	17	11	28
Viking-Red grazing crossbred	60	37	9	46	44	14	58
Viking-Red-sired crossbred	72	14	37	51	13	60	73
Total	531	190	184	374	227	352	579

[1]The study spanned 4 yrs, and some cows had multiple lactations throughout the study.

Table 2. Estrus detection performance (95% CI) of the ARS[1] compared to the gold standard of the organic and low-input conventional herds during the summer and winter breeding seasons

Item	Sensitivity	Specificity	PPV
		-------------------- % -----------------	
<u>Organic herd</u>	56.7 (52.7-60.7)	99.3 (99.2-99.4)	59.8 (55.7-63.8)
Summer	33.8 (28.6-39.5)	99.3 (99.1-99.4)	47.9 (41.0-54.8)
Winter	79.2 (74.2-83.6)	99.3 (99.1-99.4)	66.8 (61.7-71.6)
<u>Low-input conventional</u>	70.1 (66.8-73.1)	99.2 (99.1-99.3)	66.3 (63.2-69.4)
Summer	69.2 (65.1-73.2)	99.2 (99.0-99.3)	65.7 (61.5-69.7)
Winter	71.3 (66.2-76.1)	99.3 (99.2-99.4)	67.3 (62.2-72.2)

[1] HR-LD Tag, SCR Engineers Ltd., Netanya, Israel.
Sensitivity = TP/(TP+FN) x100; TP = true positive, FN = false negative
Specificity = TN/(TN+FP) x100; TN = true negative, TP = true positive, FN = false negative
Positive Predictive value (PPV) = TP/(TP + FP) x100; TP = true positive, FP = false positive

Table 3. Estrus detection performance results (95% CI) of logistic regression and SVM prediction models at a threshold of 65% predicted probability of estrus for two herds during the summer and winter breeding seasons

		Sensitivity	Specificity	PPV
			-------------------- % -----------------	
Logistic Regression, Base Model	Organic	73.0 (64.2-80.6)	94.3 (93.3-95.1)	37.6 (31.4-44.1)
	Summer	60.0 (47.6-71.5)	91.1 (89.4-92.6)	26.9 (20.1-34.6)
	Winter	90.4 (79.0-96.8)	97.4 (96.4-98.2)	58.0 (46.5-68.9)
	Conventional	82.4 (75.6-88.0)	95.9 (95.0-96.6)	55.0 (48.5-61.5)
	Summer	81.4 (72.3-88.6)	95.1 (93.9-96.1)	51.3 (43.1-59.4)
	Winter	83.9 (72.3-92.0)	97.0 (95.8-97.9)	61.9 (50.7-72.3)
Support Vector Machine, Base Model	Organic	72.1 (63.3-79.9)	95.6 (94.7-96.4)	43.6 (36.6-50.7)
	Summer	60.0 (47.6-71.5)	92.8 (91.3-94.2)	31.3 (23.6-39.9)
	Winter	88.5 (76.6-95.6)	98.3 (97.5-98.9)	67.6 (55.2-78.5)
	Conventional	79.2 (72.1-85.3)	97.7 (97.1-98.3)	68.1 (60.9-74.8)
	Summer	77.3 (67.7-85.2)	97.2 (96.2-98.0)	63.6 (54.2-72.2)
	Winter	82.3 (70.5-90.8)	98.5 (97.6-99.1)	76.1 (64.1-85.7)
Logistic Regression, Extended Model	Organic	68.9 (59.8-76.9)	96.5 (95.7-97.2)	48.0 (40.4-55.7)
	Summer	55.7 (43.3-67.6)	94.2 (92.8-95.4)	34.5 (25.8-44.0)
	Winter	86.5 (74.2-94.4)	98.7 (97.9-99.2)	72.6 (59.8-83.1)
	Conventional	79.9 (72.8-85.8)	97.8 (97.1-98.3)	68.6 (61.4-75.3)
	Summer	77.3 (67.7-85.2)	97.2 (96.2-98.0)	63.6 (54.2-72.2)
	Winter	83.9 (72.3-92.0)	98.6 (97.7-99.2)	77.6 (65.8-86.9)
Support Vector Machine, Extended Model	Organic	68.9 (59.8-76.9)	96.4 (95.7-97.1)	47.7 (40.2-55.4)
	Summer	52.9 (40.6-64.9)	94.1 (92.7-95.4)	33.0 (24.4-42.6)
	Winter	90.4 (79.0-96.8)	98.7 (97.9-99.2)	73.4 (60.9-83.7)
	Conventional	79.2 (72.1-85.3)	97.9 (97.3-98.4)	69.6 (62.4-76.2)
	Summer	76.3 (66.6-84.3)	97.5 (96.6-98.2)	66.1 (56.5-74.7)
	Winter	83.9 (72.3-92.0)	98.4 (97.4-99.1)	75.4 (63.5-84.9)

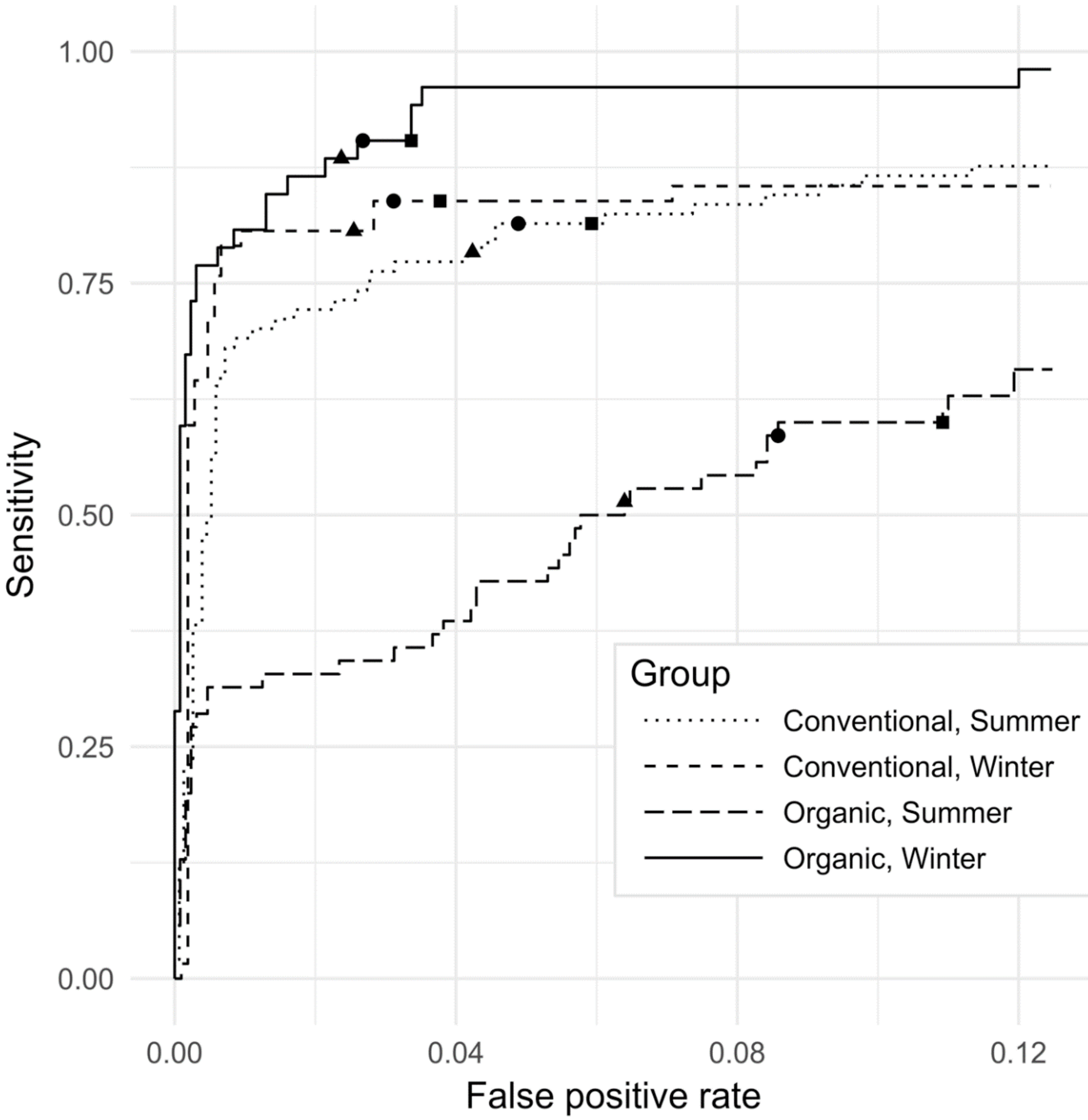

Figure 1. ROC curves of the base logistic regression model. Threshold of the predicted probability for estrus at 60% (■), 65% (●), and 70% (▲).

MANUSCRIPT 3

Short communication: Activity and rumination of Holstein versus crossbred cows in an organic grazing and low-input conventional dairy herd.

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INTERPRETIVE SUMMARY

Short communication: **Activity and rumination of Holstein versus crossbred cows in an organic grazing and low-input conventional dairy herd. Pereira and Heins, (2018).** The activity and rumination of organic grazing and low-input conventional lactating dairy cattle were compared for Holstein and crossbred dairy cows across 4 yrs. Daily activity of both the organic grazing and low-input conventional herds was greater during the summer months and decreased during the winter months. Conversely, daily rumination of both herds was greater during the winter months and lower during the summer months. Activity and rumination varied by breed groups within both herds.

SUMMARY

Holstein and crossbred dairy cows from an organic grazing and low-input conventional herd were evaluated for activity and rumination across a 4 yr time period. Data spanned from January 2014 to December 2017 at the University of Minnesota West Central Research and Outreach Center, Morris, MN organic grazing (ORG) and low-input conventional (CONV) herd. Breed groups were comprised of: Holstein (HO; n = 114), HO maintained at 1964 breed average level (H64; n = 83); crossbreds comprised of Montbéliarde, Viking Red, and HO (MVH; n = 248), and crossbreds comprised of Normande, Jersey, and Viking Red (NJV; n = 167). During the summer grazing season (May to October) organic (ORG) cows were on pasture and supplemented daily with 2.72 kg of corn per cow, and conventional (CONV) cows were fed a TMR in an outdoor confinement dry-lot. During the winter season (November to April) ORG and CONV cows were fed a TMR consisting of corn silage, alfalfa haylage, corn, soybean meal, and minerals in an outwintering lot and a compost barn. Activity (reported in activity units by daily and bihourly periods) and rumination, (min/d and min/2 h) from SCR DataFlow II software, were monitored electronically using HR-LD Tags (SCR Engineers Ltd., Netanya, Israel) for the 4 yr period. For activity and rumination analysis with PROC HPMIXED of SAS, independent variables were herd (ORG or CONV), month (January to December), breed group (HO, H64, MVH, NJV), parity group (1 or 2+), and two and three way interactions of herd, month, breed group and parity group. Cow nested within breed group and herd was a random effect. Holstein and crossbred cows were not different for activity in the ORG and CONV herds. The H64 cows had lower rumination than the other breed groups in the ORG and CONV herds. For ORG primiparous cows, the H64 cows had lower rumination (495 min/d) than HO (520 min/d) cows, and the ORG multiparous H64 cows had lower rumination (496 min/d) than other multiparous breed groups. For CONV primiparous cows, the H64 cows had lower rumination (478 min/d) than HO (498 min/d) and MVH (497 min/d) cows, and the CONV multiparous H64 cows had lower rumination (489 min/d) than other multiparous breed groups. The HO and crossbred cows predominantly ruminated during the evening and overnight hours in both herds.

Keywords: crossbreeding, organic, grazing, rumination

SHORT COMMUNICATION

Activity and rumination may provide insight on the comfort and health status of dairy cattle. In confinement dairy systems the continuous monitoring of activity and rumination with an activity and rumination monitoring system **(ARS)** was beneficial by detecting cows in estrus (Madureira et al., 2015). During the transition period, decreased rumination time may indicate cows that can be predisposed to subclinical diseases or health disorders (Soriani et al., 2012). For pasture-based dairy herds, Elischer et al. (2013) validated an ARS system in an automated milking grazing Holstein **(HO)** herd and found that the ARS recorded activity and rumination, but with low accuracy. In New Zealand, where intensive grazing systems are most popular, an ARS system was valuable for estrus detection in herds needing to improve their estrus detection rate (Kamphuis et al., 2012).

Many grazing farmers prefer crossbred cows to HO cows because they have longer productive life and enhanced fertility (Heins and Hansen, 2012; Heins et al., 2012; Buckley et al., 2014). Gregorini et al. (2013) reported no differences among breed, genetic merit and rumination of HO compared with HO x Jersey **(JE)** crossbred cows. However, Bae et al. (1983) reported that rumination may be affected by breed and body size. Rumination of HO, JE and crossbreds of JE x HO was different between the 3 breed groups based on body weight in a New Zealand study (Prendiville et al., 2010). Few studies have compared breed groups for activity and rumination in the US. One study reported that HO was not different from JE or crossbreds of HO and JE for activity in first lactation; however, HO cows had lower activity than crossbred cows in later lactations (Stone et al., 2017).

The increased global interest in crossbreeding has allowed dairy breeds such as the Normande, Montbéliarde and Viking Red to be evaluated in the United States (Heins et al., 2012; Hazel et al., 2014). In a grass-based production system, milk production was similar for HO and Montbéliarde × HO and Normande × HO crossbred dairy cows (Walsh et al., 2008). To our knowledge daily activity and rumination of HO and crossbred cows comprised of Montbéliarde, Normande, and Viking Red has not yet been reported. Montbéliarde × HO crossbred cows have greater BCS compared to HO cows (Hazel et al., 2014) and the ARS may record behaviors differently when comparing dairy breeds. The objective of this study was to evaluate the daily and bihourly activity and rumination of Holstein and crossbred dairy cows in an organic grazing herd and low-input conventional herd.

This study was conducted from January of 2014 to December of 2017 at the University of Minnesota West Central Research and Outreach Center, Morris, MN and animal care and management were approved by the University of Minnesota Institutional Animal Care and Use Committee (#1508-32966A). The experimental research herd is a

300-cow dairy that is split into an organic herd **(ORG)** and low-input conventional herd **(CONV)**. Cows were milked twice per d in a swing-9 parabone-milking parlor. The ORG herd was milked at 0600 h in the morning, followed by the CONV herd at 0800 h and the ORG herd was milked at 1700 h in the evening followed by the CONV herd at 1900 h.

During the grazing season (May to October), the ORG herd grazed on pasture for 22 h/d in accordance with the National Organic Program pasture rule (USDA-NOP, 2017), which requires organic dairy cattle to graze for at least 120 d and receive 30% of their daily DMI from pasture. The pastures were comprised of a mixture of diverse grasses and legumes that included smooth bromegrass, orchardgrass, meadow fescue, alfalfa, red clover, white clover, and kura clover. Cows were stocked at a rate of 3 cows/ha and were rotated to new paddocks every 2 d based on forage availability. In addition to pasture, each ORG cow was supplemented with 2.72 kg of organic corn daily and had free-choice access to minerals from a feeder placed at ground level in each paddock. Cows had ad libitum access to water from a water trough also placed at ground level in each paddock. During the winter months (November to April), ORG cattle were moved to an outwintering lot (Heins et al., 2018), and fed a TMR consisting of corn silage, alfalfa haylage, corn, soybean meal, and minerals. For the CONV herd, cattle were fed a TMR consisting of corn silage, alfalfa haylage, corn, soybean meal, and minerals in an outdoor confinement dry-lot during the summer and a compost-bedded pack barn during the winter (Heins et al., 2018).

The ORG and CONV herds calved seasonally and were bred to maintain a seasonal production system. Calving seasons were spring (March to May) or autumn (September to November) and breeding seasons were summer (June to August) or winter

(December to February). Cows in both herds were culled based on strict management decisions, and cows were culled based on fertility, SCS, and production level. If cattle did not become pregnant within 2 breeding seasons (6 months total), they were culled for poor fertility.

The University of Minnesota West Central Research and Outreach center research herd began crossbreeding during 2000 when pure HO heifers and cows were randomly assigned to either a HO line or crossbred line. The heifers and cows in the HO line were mated to HO AI bulls, and the HO heifers and cows in the crossbred line were mated to JE AI bulls. All JE × HO crossbred heifers and cows were mated to Montbéliarde bulls to initiate a 3-breed rotational system. Subsequently in 2002, some HO multiparous cows were also mated to Montbéliarde AI bulls to provide comparison of HO and Montbéliarde x HO crossbreds. The HO cows were randomly mated to either Montbéliarde AI bulls or HO AI bulls. Initially, the Montbéliarde × HO were mated to JE AI bulls; however, recently the Montbéliarde × HO cows were mated to Viking Red AI bulls, based on shortcomings of the JE breed in a confinement rotational crossbreeding system (Heins et al., 2011). All 3-breed crossbreds were mated to HO AI bulls to create a 3-breed crossbreeding rotation of Holstein, Montbéliarde and Viking Red.

Another 3-breed crossbreeding rotation was developed beginning in 2005 for the ORG and CONV herds. During 2003, a herd of JE × HO crossbred heifers were purchased to initiate a crossbreeding rotation that would improve longevity, fertility, and health traits for grazing dairy cattle. The JE × HO crossbred heifers were bred to Norwegian Red and Viking Red AI bulls. The resulting offspring were bred to Normande AI bulls, and the Normande-sired crossbred heifers and cows were mated to JE AI bulls to create a 3-breed crossbreeding rotation of Viking Red, Normande and JE. Figure 1 provides a visual description of the 2 crossbreeding breeding rotations.

Three AI bulls were selected annually based on high ranking with the US Net Merit index (Holstein and Jersey; VanRaden, 2017), with the French ISU total merit index (Montbéliarde, Montbéliarde Association, 2018; and Normande; Organisme de Sélection en Race Normande, 2018) and with the Nordic Cattle NTM (Viking Red; Nordisk Avlsvaerdi Vurdering, 2018). Inbreeding coefficients were not allowed to surpass 6.25% for matings of HO heifers and cows with HO sires. The 1964 Holstein control (**H64**) population design is described in Hansen (2000). For this study HO cows were compared with H64, crossbred cows of HO, Montbéliarde, and Viking Red (**MVH**), and crossbred cows of Normande, Jersey, and Viking Red (**NJV**).

At calving, all cows were equipped with an HR-LD tag activity and rumination collar (SCR Engineers, Netanya, Israel) around the neck (Schirmann, et al., 2009). Activity (reported in activity units by daily and bihourly periods) and rumination (reported in minutes/d and min/2 h period) were monitored by a tri-axial accelerometer, microphone and microprocessor contained within the collar tag (Sjostrom et al., 2016; Dolecheck et al., 2015). The ARS transferred data to a long distance antenna placed atop the milking parlor. Each time the cattle returned to the milking center and if they were in pasture near the milking center, the antenna would download data as often as every 20 min. The data were sent to the computer in the farm office and processed through the SCR DataFlow II software (Data Flow Software, SCR Engineers, Netanya, Israel).

Cow data (herd, lactation number, calving date) was retrieved from PCDart software (Dairy Records Management Systems, Raleigh, NC) on the farm. Lactations greater than 5 were excluded from the analysis. The UNIVARIATE procedure of SAS 9.4 (SAS Institute Inc., Cary, NC) was used to establish normality of daily activity and rumination data before statistical analysis. If daily activity was less than 100 units and greater than 2,500 activity units, the data were removed from analysis. For daily rumination, observations that were less than 30 min/d and greater than 1080 min/d were removed from analysis. In addition, observations were deleted if the bihourly data were less than 5 units per 2 h for activity and less than 5 min per 2 h for rumination. Potential reasons for missing and abnormal data include data not being properly read from the collars to the barn antenna, ARS collars malfunctioning due to wear and tear, or a ARS collar may have been lost from a cow.

Overall, 612 HO and crossbred cows were used for analysis (Table 1). The number of first lactation observations (n=509) were considered a primiparous group and lactation numbers 2 to 5 (n=820) were combined into a single multiparous group. The study included data from 114 HO, 83 H64, 248 MVH crossbreds and 167 NJV crossbreds across both herds.

For daily activity and rumination, independent variables were herd (ORG or CONV), month (January to December), breed group (HO, H64, MVH, NJV), parity group (primiparous and multiparous), two and three way interactions of herd, month, breed group and parity group. For bihourly activity and rumination analysis, independent variables were herd, month, breed group, parity group, time (0000 h to 2400 h, in two hour intervals), two and three way interactions of herd, month, time, breed group and parity group. Cow nested within breed group and herd was a random effect. The PROC

HPMIXED of SAS (SAS Institute, 2014) was used to obtain solutions and conduct the ANOVA. Differences were considered significant at $P < 0.05$.

Least squares means and standard errors for daily activity and rumination for month and herd are in Table 2. For daily activity, month, parity group, the interactions of parity group by breed group, herd by month and herd by breed group and month significantly explained variation ($P < 0.01$). For daily rumination, herd, month, breed group, parity group, and the interactions of parity group by breed group, herd by month and herd by breed group and month significantly explained variation ($P < 0.01$).

The daily activity and rumination for the ORG herd was 614 and 514 min/d, respectively. For daily activity of the ORG herd, cows in July (924) had greater ($P < 0.01$) activity compared to the other months of the year. Daily activity increased during the grazing season (May to October) for the ORG herd and decreased in October when the cows were loosely confined in an outwintering lot. Sjostrom et al. (2016) evaluated ORG grazing cattle in a research herd and reported greater daily activity during the month of July compared to the other summer months, with a decrease in activity for September. For daily rumination for the ORG herd, cows in February (544 min/d) had greater ($P < 0.01$) rumination compared to the other months. Daily rumination decreased ($P < 0.01$) during July (437 min/d) for the ORG herd and increased during September (518 min/d). The decrease in rumination during periods of heat stress has been thoroughly documented (Soriani et al., 2013). In addition, grazing cattle may reduce rumination to optimize grazing time (Gregorini et al., 2012), especially during the hot summer months.

The overall daily activity and rumination of the CONV herd was 608 and 504 min/d, respectively. For daily activity by month for the CONV herd, cows in July (867) had greater ($P < 0.01$) daily activity, and daily activity increased during the summer months of June (736) and August (759) and decreased during the winter months of December (442), January (465) and February (479). For daily rumination for the CONV herd, February (514 min/d) had the highest ($P < 0.01$) rumination and March (478 min/d) had the lowest. Daily rumination did not change as drastically for the CONV herd during the summer months compared to the ORG herd, ranging from 505 to 509 min/d. Cattle in the CONV herd experienced similar environmental conditions as the ORG herd, and the increase in activity during the summer months may be due to fly avoidance behaviors (Sjostrom et al., 2016).

The means for bihourly activity (units/2 h) are in Figure 2 and rumination (min/2 h) in Figure 3 for the ORG and CONV herd. Both herds increased activity levels starting at 0400 h and throughout the day until 1800 h. Activity from 0400 h to 0600 h for the ORG herd was greater ($P < 0.01$) than the CONV herd, and this was the time ORG cows were brought to the milking parlor for milking. In the ORG herd, after the morning milking, activity decreased from 0800 h to 1000 h. The results are similar to Sjostrom et al. (2016), who reported activity increased and rumination decreased after the morning milking for an organic dairy grazing herd. In 2006, a study from New Zealand analyzed grazing time of rotationally grazed cows provided fresh pasture after milking. The study reported that 94% of cows grazed for 1 h after a.m. milking and grazing activity declined after the first hour of grazing; however, following the p.m. milking, 87% of cows continuously grazed for longer, until sunset (Sheahan et al., 2013). Both ORG and CONV herds were active during the day time and ruminated during the evening and night. Gregorini et al. (2012) found similar results in a study conducted during 2008 in New Zealand, where cows on pasture ruminated during the night time.

Table 3 has the least squares means and standard errors for daily activity and rumination for breed groups by herd. For the ORG herd, daily activity was similar for all breed groups. For daily rumination, H64 (495 min/d) cows ruminated less ($P < 0.05$) compared to the HO (529 min/d), MVH (519 min/d) and NJV (513 min/d) crossbreds. Although both H64 and HO cattle are purebred HO, they are genetically different. Milk production for the H64 cows is drastically lower than HO cows and body size is smaller for H64 cows compared with HO cows (Hansen, 2000), which may have affected daily rumination.

For the CONV herd, daily activity was similar between all breed groups. For daily rumination of the CONV herd, H64 (483 min/d) cows ruminated less ($P < 0.05$) compared to the HO (512 min/d), MVH (507 min/d) and NJV (512 min/d) crossbreds. Rumination time has been described to depend on bolus size and smaller boluses take less time to chew. In the study by Prendiville et al. (2010), JE cattle tended to regurgitated a new bolus 28 s faster than the HO cattle which allowed JE cattle to ruminate for a shorter amount of time. The current study is in agreement with Stone et al. (2017) who reported no difference in activity between HO and crossbred cows in first lactation. However, activity was greater for crossbred cows in later lactations compared with HO cows in the study by Stone et al. (2017), which is contrary to the current study.

Table 4 has means and standard errors for daily activity and rumination for breed groups and herd by parity group. Daily activity for the ORG and CONV herd was variable across the primiparous and multiparous HO and crossbred cows. The primiparous HO and crossbred cows in the CONV herd did not differ for daily activity. For daily rumination for the multiparous cows in the ORG and CONV herd, the H64 cows were lower ($P < 0.05$) compared with the HO, MVH, and NJV cows. For the primiparous cows in both the ORG and CONV herd, the H64 and NJV cows were not different ($P > 0.05$) for daily rumination.

Activity and rumination of HO and crossbred cows may provide insight into cow comfort and animal health and well-being of dairy cattle. The large number of HO and crossbred cows in this study provides a reliable source for activity and rumination that may be used as a reference by pasture-based and low-input dairy production systems in the Upper Midwest and the US. Activity from the ARS system may not be important to measure the health and well-being of dairy cows. However, based on numerous validation studies of ARS systems (Schirmann et al., 2009; Elsicher et al., 2013, Pereira et al., 2018) rumination may be a better indicator of health status of HO and crossbred cows. Rumination may be an indicator of DMI in cattle and can pro-vide a measure of feeding behavior of cattle to improve productivity and profitability of HO and crossbred dairy cows.

Although differences for rumination were only found between HO and H64 cows in the study, it is also important to know the similarities between HO and crossbred cows for activity and rumination. Dairy producers that plan to utilize ARS in their dairy herd can be assured that the system will work for various breeds of cattle in various management systems. The herd differences that are reported in the current study are important because the results of activity and rumination will provide insight for dairy producers that have HO or crossbred cows in an ORG or CONV dairy production system.

CONCLUSION

The current study is the first study to provide insight into the activity and rumination behavioral patterns of HO and crossbred dairy cows. The daily activity was similar across the parities and breed groups. The H64 cows had greater differences of rumination time compared with the HO and crossbred cows. The activity and rumination differences observed in this study provide novel information into the effects that the HO and crossbreds have in organic and low-input dairy herds. Similar activity and rumination time were observed within breeds, and therefore, ARS can be used to record activity and rumination in crossbred cows.

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Table 1. Number of cows and lactation observations[1] by specific breed groups for the organic and low-input conventional dairy herds at the University of Minnesota West Central Research and Outreach Center, Morris, MN

	Total number of cows	Primiparous			Multiparous		
		Organic	Conventional	Total	Organic	Conventional	Total
<u>Breed</u>							
Holstein	114	18	70	88	18	143	161
1964 Holstein	83	37	23	60	60	50	110
MVH[2]	248	70	148	218	82	257	339
NJV[2]	167	118	25	143	171	39	210
Total	612	243	266	509	331	489	820

[1]Because this study spanned across 4 yrs, some cows may have multiple lactations throughout the study.
[2] MVH = crossbreds of Montbéliarde, Viking Red, and Holstein; NJV = crossbreds of Normande, Jersey, and Viking Red

Table 2. Least squares means and standard errors for daily activity and rumination by month across the organic dairy herd and low-input conventional dairy herd

	Organic herd				Conventional herd			
	Daily activity	SE	Daily rumination	SE	Daily activity	SE	Daily rumination	SE
Month	--(activity units)--		---- (min/d)----		--(activity units)--		---- (min/d)----	
January	467[a]	16.3	534[a]	3.7	465[a]	15.3	508[a]	3.4
February	491[b]	16.4	544[b]	3.7	479[b]	15.3	514[b]	3.5
March	513[c]	16.3	521[c]	3.7	540[c]	15.4	478[c]	3.5
April	574[d]	16.3	544[a,d]	3.6	604[d]	15.3	493[d]	3.4
May	706[e]	16.3	536[e]	3.6	658[e]	15.2	509[e]	3.4
June	843[f]	16.3	474[f]	3.6	736[f]	15.2	509[e,f]	3.4
July	924[g]	16.3	437[g]	3.6	867[g]	15.2	505[a,g]	3.4
August	735[h]	16.4	497[h]	3.7	759[h]	15.2	506[a,g,h]	3.4
September	654[i]	16.4	518[c,i]	3.7	680[i]	15.2	503[a,g,i]	3.4
October	518[c,j]	16.3	524[c,j]	3.7	554[j]	15.2	500[j]	3.3
November	493[b,k]	16.3	525[c,j,k]	3.6	515[k]	15.2	507[a,e,g,h,k]	3.3
December	452[l]	16.3	532[a,l]	3.6	442[l]	15.2	509[a,e,k,l]	3.4
Across months	614	16.1	514	3.5	604	15.0	504	3.2

[a-l]= Means within a herd for daily activity and daily rumination without common superscripts are different at $P < 0.05$

Table 3. Least squares means and standard errors for daily activity and rumination by breed group across lactation numbers for the organic dairy herd and low-input conventional dairy herd

	Organic herd				Conventional herd			
	Daily activity	SE	Daily rumination	SE	Daily activity	SE	Daily rumination	SE
Breed group	--(activity units)--		---- (min/d)----		--(activity units)--		---- (min/d)----	
Holstein	636	49.1	529[a]	10.6	579	21.2	512[a]	4.6
1964 Holstein	623	29.6	495[b]	6.4	585	36.3	483[b]	7.8
MVH	580	23.9	519[a]	5.1	616	15.9	507[a]	3.4
NJV	621	17.7	513[a]	3.8	643	40.2	512[a]	8.6

[a-b]= Means within a herd for daily activity and daily rumination without common superscripts are different at $P < 0.05$
[1]MVH = crossbreds of Montbéliarde, Viking Red, and Holstein; NJV = crossbreds of Normande, Jersey, and Viking Red

Table 4. Least squares means and standard errors for daily activity and rumination by breed group for primiparous and multiparous cows for the organic dairy herd and low-input conventional dairy herd

	Organic herd				Conventional herd			
Breed group	Primiparous		Multiparous		Primiparous		Multiparous	
Activity (activity units)	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Holstein	516[a,b]	49.1	730[a,b]	49.2	502[a]	21.2	667[a]	21.2
1964 Holstein	608[b]	29.7	664[b]	29.7	567[a]	36.4	590[a,b]	36.3
MVH	538[b]	23.9	621[a]	24.0	577[a]	15.9	656[b]	15.9
NJV	614[a]	17.6	621[a]	17.7	575[a]	40.1	734[b]	40.2
Rumination (min/d)								
Holstein	520[a]	10.6	538[a]	10.7	498[a]	4.6	525[a]	4.6
1964 Holstein	495[b]	6.5	496[b]	6.5	478[b]	7.9	489[b]	7.8
MVH	519[b]	5.2	519[a]	5.2	497[a]	3.4	518[a]	3.4
NJV	510[a,b]	3.8	517[a]	3.8	500[a,b]	8.6	523[a]	8.7

[a-b]= Means within a herd for daily activity and daily rumination without common superscripts are different at $P < 0.05$

[1]MVH = crossbreds of Montbéliarde, Viking Red, and Holstein; NJV = crossbreds of Normande, Jersey, and Viking Red

Figure 1. University of Minnesota West Central Research and Outreach Center breeding design for the organic dairy herd and low-input conventional dairy herd. MVH = crossbreds of Montbéliarde, Viking Red, and Holstein; NJV = crossbreds of Normande, Jersey, and Viking Red

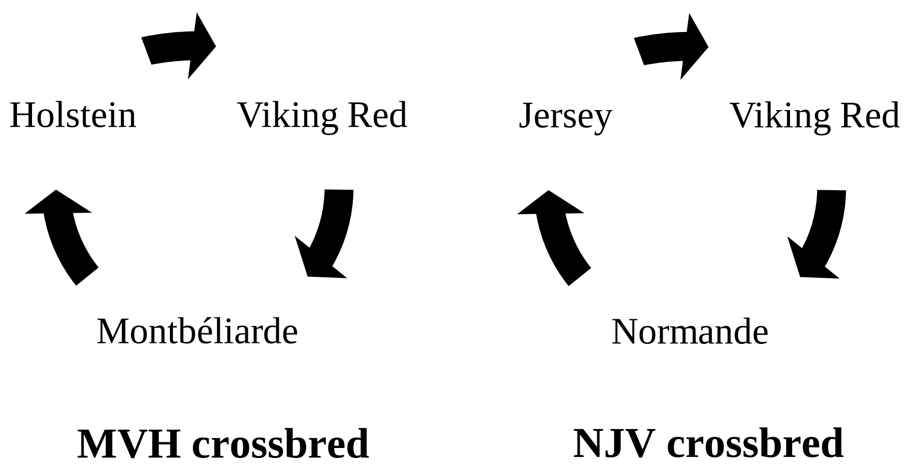


Figure 2. Least squares means and standard error bars for activity index by 2-h intervals for the organic dairy herd (▲ =ORG) and low-input conventional dairy herd (■ =CONV). **P < 0.01 for difference.

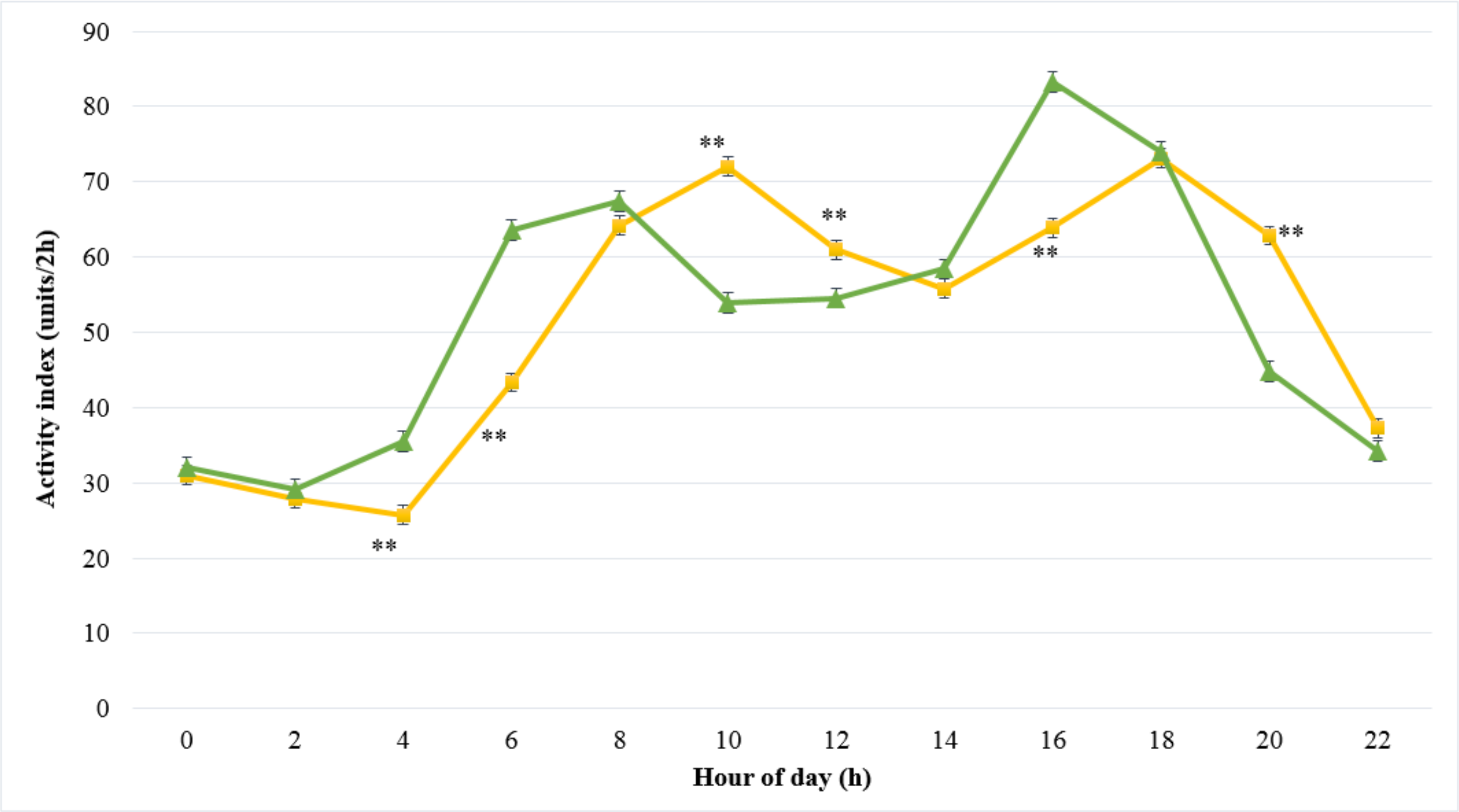
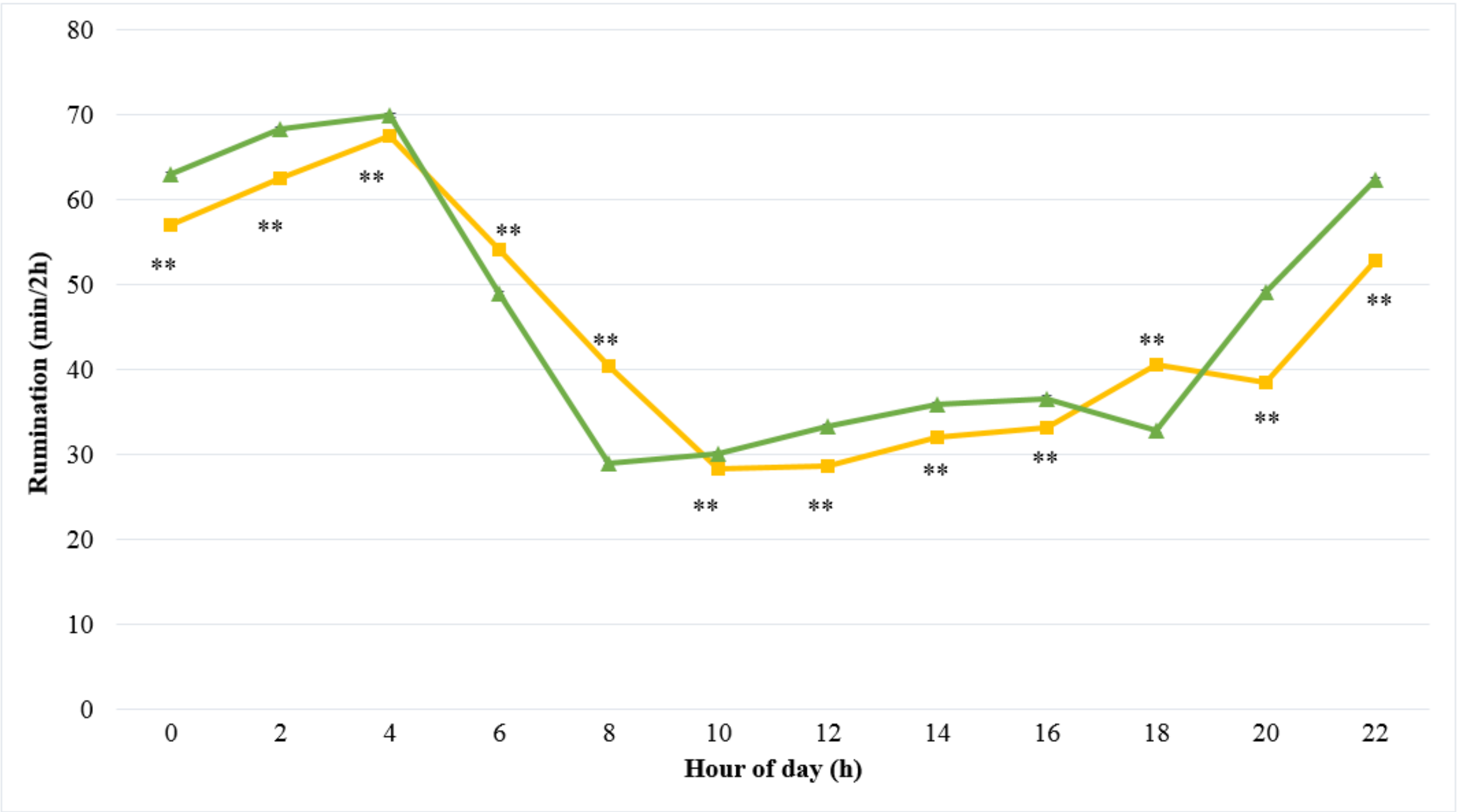


Figure 3. Least squares means and standard error bars for rumination by 2-h intervals for the organic dairy herd (▲ =ORG) and low-input conventional dairy herd (■ =CONV). ***P* < 0.01 for difference.



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